Decision under uncertainty

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Master courses

A game to start with

Did I drink tea this morning?

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You win 100 euros if I had tea this morning. What's the max you would bet on it?

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Ok, now your neighbour can buy/sell as many tickets as he/she wants. His/her task is, if possible, to be sure to win money.

Outline

- Basics
- Probabilities as bets
- Going beyond betting probabilities: why and how?
- Probability sets, a.k.a. credal sets
- Practical models and computations
- Decision with probability sets

Basic modelling

- The state X of the world
  - take values in some (finite or not) set $\mathscr{X}$ of possible situations
  - $\mathscr{X}$ assumed exhaustive and of sufficient granularity
  - is uncertainly known
- How to model our uncertainty about X?
  - by probabilities $\rightarrow$ why???

Basic definitions

Basic tool

A probability distribution $p : \mathscr{X} \to [0,1]$ such that

- $p(x) \geq 0$
- $\sum_x p(x) = 1$

from which for any subset we have

- $P(A) = \sum_{x \in A} p(x)$
- $P(A) = 1 - P(A^c)$: auto-dual

Example

Academic dice Assume a dice, we have $\mathscr{X} = \{1,2,\dots,6\}$:

$$p(1) = p(2) = p(3) = p(4) = p(5) = p(6) = 1/6$$

$$P(\{1,3,5\}) = 1/6 + 1/6 + 1/6 = 1/2$$

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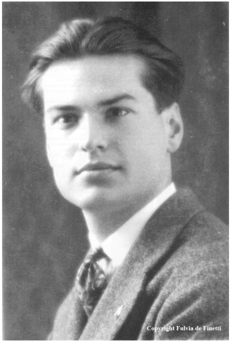
Three important guys



L. Savage J. Von Neumann **B. De Finetti**

All justify probabilities (and expected utilities) as uncertainty models without frequencies → we will detail a bit how the second one does it

An example

A gamble/ticket f, whose reward depends on who win the most sets in next Rolland Garros




	Nadal	Ruud	Cilic	Djokovic
f=	-2	10	0	5

What price $P(f)$ do you associate to this ticket?

Acceptable transaction

The price

$$P(f)$$

is the "fair" price you associate to the ticket/gamble f:

- You would buy for any price $P(f) - \epsilon$, earning

$$f - (P(f) - \epsilon)$$

- You would sell for any price $P(f) + \epsilon$, earning

$$(P(f) + \epsilon) - f$$

$\rightarrow$ how should a "rational" agent specify prices?

Transaction on an event

Remember the bet on tea?

Betting on an event A amounts to play the gamble

$$\mathbb{I}_A = \begin{cases} 1 & \text{if } A \text{ happens} \\ 0 & \text{else} \end{cases}$$

We can use A and $\mathbb{I}_A$ interchangeably, i.e.

$$P(\mathbb{I}_A) = P(A)$$

Avoiding the dutch book[1]

- A set of gambles $f_1, \dots, f_n$
- **You** set prices $P(f_1), \dots, P(f_n)$
- I can sell ($\lambda_i > 0$) or buy ($\lambda_i < 0$) to you any number of gambles
- **You** are **irrational** if there is a dutch book, i.e., a combination with

$$\sup_{x \in \mathscr{X}} \sum \lambda_i \Big(f_i(x) - P(f_i) \Big) < 0,$$

  meaning that whatever happens, you lose money.
- so, a **rational** agent should avoid sure losses when setting prices $P(f_1), \dots, P(f_n)$

[1] History unclear

Probabilities and expectations (exercices)

Do the following:

- Prove that if you are rational, then $\inf f \leq P(f) \leq \sup f$
- Prove that if you are rational, then $P(f+g) = P(f) + P(g)$
- Deduce that $P(A \cup B) = P(A) + P(B)$ if $A \cap B = \emptyset$

A little bit more:

- Show that $\sum_{x \in \mathcal{X}} P(\{x\}) = 1$
- Show that $P(f) = \sum_{x \in \mathcal{X}} f(x) P(\{x\})$

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- Show that $P(f) = \sum_{x \in \mathcal{X}} f(x) P(\{x\})$

The first and second properties/axioms are enough to characterize probabilities and expectations.

Wrap-up so far

Subjective probabilities[2]:

- Betting behaviour in terms of fair price reflect (can be used to measure) your knowledge about the world
- If you are rational, those bets should conform with probabilities and expected utilities
- Those bets can be given for all kinds of events, including those that will happen only once

Yet, maybe there is a little more to the story.

[2]Often taken as an interpretation for Bayesian approaches

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  - Rationality
  - Some axiomatics
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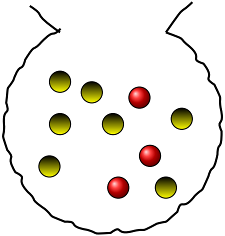
Experimental protocol

- Half the room goes out
- The rest pick a choice
- We exchange (inside goes outside, and vice-versa)

Urns and balls: case 1

9 balls, 3 are reds, 6 remaining are either yellow or black



What would you choose between A and B?

A

R(ed)	B(lack)	Y(ellow)
100 $	0 $	0$

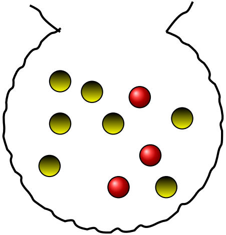
B

R(ed)	B(lack)	Y(ellow)
0 $	100 $	0$

Interlude during the change

Urns and balls: case 2

9 balls, 3 are reds, 6 remaining are either yellow or black



What would you choose between C and D?

C

R(ed)	B(lack)	Y(ellow)
100 \$	0 \$	100\$

D

R(ed)	B(lack)	Y(ellow)
0 \$	100 \$	100\$

An illustration of a possible use (more latter)

Is it a lioness? a cat? a puma? a bobcat?

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Are buying and selling the same?

What if we considered that buying and selling prices for f modelling your knowledge could differ?

- For f, we now consider a maximal buying price $\underline{P}(f)$
- Meaning you would **buy** f for any price under $\underline{P}(f)$
- Any transaction $f - (\underline{P}(f) - \epsilon)$ is acceptable/desirable
- More formally:

$$\underline{P}(f) = \sup\{x \in \mathbb{R} : f - x \text{ is acceptable }\}$$

Why not caring about selling prices?

- $\overline{P}(f)$ is your minimal selling price for f:

$$\overline{P}(f) = \inf\{x \in \mathbb{R} : x - f \text{ is acceptable }\}$$

- Yet, we do have[3]:

$$\begin{aligned}
\underline{P}(f) &= \sup\{x \in \mathbb{R} : f - x \text{ is acceptable }\} \\
&= -\inf\{-x \in \mathbb{R} : f - x \text{ is acceptable }\} \\
&= -\inf\{y \in \mathbb{R} : f + y \text{ is acceptable }\} \\
&= -\inf\{y \in \mathbb{R} : y - (-f) \text{ is acceptable }\} \\
&= -\overline{P}(-f)
\end{aligned}$$

- By duality, we can only deal with buying prices.

[3] Note that it does not imply $\overline{P}(f) = \underline{P}(f)$

Being a rational agent: sure loss revisited

- A set of gambles $f_1, \ldots, f_n \in \mathcal{K}$
- **You** set prices $\underline{P}(f_1), \ldots, \underline{P}(f_n)$
- I can sell[4] ($\lambda_i > 0$) to you any number of gambles for these price or lower
- **You** are **irrational** and incur sure loss if there is a combination

$$\sup_{x \in \mathcal{X}, \lambda_i > 0} \sum \lambda_i \Big(f_i(x) - \underline{P}(f_i) \Big) < 0$$

- so, a **rational** agent should avoid sure loss when setting prices $\underline{P}(f_1), \ldots, \underline{P}(f_n)$
- It is strictly weaker than previously.

[4] But not buy anymore

Back to tennis

	Nadal (a)	Ruud (b)	Cilic (c)	Djokovic (d)
f_i	$\mathbb{I}_{\{a\}}$	$\mathbb{I}_{\{b\}}$	$\mathbb{I}_{\{c\}}$	$\mathbb{I}_{\{d\}}$
$\underline{P}(f_i) =$	0.35	0.2	0.3	0.2

Are those assessments rational? Why?

Being a reasoning agent: natural extension

- Assume prices $\underline{P}(f_i)$ avoid sure loss
- Consider a new gamble/function g
- What can I deduced about $\underline{P}(g)$ from $\underline{P}(f_i)$?
- The process of **natural extension** provides the answer:
  - Knowing that $f_i - \underline{P}(f_i)$ are acceptable
  - Find the highest price $\underline{P}'(g)$ making $g - \underline{P}'(g)$ acceptable
  - This amounts to solve

$$\underline{P}'(g) = \sup_{\alpha \in \mathbb{R}, \lambda_i \geq 0} \{\alpha : g - \alpha \geq \sum_i \lambda_i (f_i - \underline{P}(f_i))\}$$

  - We know $g - \alpha$ acceptable, because $\sum_i \lambda_i (f_i - \underline{P}'(f_i))$ acceptable
- Applying this to f_i itself, I say that prices $\underline{P}(f_i)$ are **coherent** if

$$\underline{P}'(f_i) = \underline{P}(f_i), \quad \forall f_i$$

Tennis again, rational assessments

				
	Nadal (a)	Ruud (b)	Cilic (c)	Djokovic (d)
f_i	$\mathbb{I}_{\{a\}}$	$\mathbb{I}_{\{b\}}$	$\mathbb{I}_{\{c\}}$	$\mathbb{I}_{\{d\}}$
$\underline{P}(f_i) =$	0.35	0.15	0.2	0.2
f_i	$\mathbb{I}_{\{b,c,d\}}$	$\mathbb{I}_{\{a,c,d\}}$	$\mathbb{I}_{\{a,b,d\}}$	$\mathbb{I}_{\{a,b,c\}}$
$\underline{P}(f_i) =$	0.5	0.7	0.6	0.6

Are those assessments coherent? Why?

Outline

A bit of vocabulary

- $\underline{P}(f), \overline{P}(f)$ often called **lower/upper previsions**,
- A rational $\underline{P}(f)$ is said to **avoid sure loss**
- $\underline{P}(f)$ that are deductively closed (= their natural extension) are called **coherent**
- When it is the case and for reasons that will become clear,, $\underline{P}(f), \overline{P}(f)$ also called **lower/upper expectations**
- Similarly, $\underline{P}(\mathbb{I}_A) = \underline{P}(A)$ and $\overline{P}(\mathbb{I}_A) = \overline{P}(A)$ are called **lower/upper probabilities**

Coherence through betting on linear spaces

- assume space $\mathcal{K}$ of gambles is linear

$$g, f \in \mathcal{K} \implies f + g \in \mathcal{K}$$
$$g \in \mathcal{K}, \alpha g \in \mathcal{K} \text{ for } \alpha \geq 0$$

- Then $\underline{P}$ is coherent if and only if

$$\underline{P}(f) \geq \inf f \text{ (sure bet)}$$
$$\underline{P}(\lambda f) = \lambda \underline{P}(f) \text{ (positive homogeneity)}$$
$$\underline{P}(f+g) \geq \underline{P}(f) + \underline{P}(g) \text{ (super-additivity)}$$

- You get back De Finetti probabilities (a.k.a. linear previsions) if super-additivity becomes additivity

Coherence through desirability

- A gamble f is desirable if $\underline{P}(f) = 0$
- A set $\mathscr{D}$ of desirable gambles is coherent if and only if

$$\text{If } \sup f \leq 0, \text{ then } f \not\in \mathscr{D}, \text{ if } f > 0, \text{ then } f \in \mathscr{D}$$
$$\text{If } f, g \in \mathscr{D}, \text{ then } f + g \in \mathscr{D}$$
$$\text{If } f \in \mathscr{D}, \text{ then } \lambda f \in \mathscr{D} \text{ if } \lambda \geq 0$$

- Mathematically, a set $\mathscr{D}$ is coherent if it forms a cone.

Coherence through desirability

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$$\text{If } f \in \mathscr{D}, \text{ then } \lambda f \in \mathscr{D} \text{ if } \lambda \geq 0$$

- Mathematically, a set $\mathscr{D}$ is coherent if it forms a cone.

Coherence through probability sets (we will stick with that)

- We can interpret $\underline{P}(f)$ as a lower bound on expectation for probabilities, i.e.,

$$\underline{P}(f) \leq P(f) = \sum_x p(x)f(x)$$

where p is a probability mass ($\sum p(x) = 1$ and $p(x) \geq 0$).

- Given $f_1, \ldots, f_n$ and $\underline{P}(f_i)$, we can define a set of dominating probabilities (a.k.a. credal sets)

$$\mathscr{M}(\underline{P}) = \{P : P(f) \geq \underline{P}(f)\}$$

- $\underline{P}$ avoids sure loss if and only if $\mathscr{M}(\underline{P}) \neq \emptyset$
- $\underline{P}$ is coherent if and only if for any f_i, we have

$$\underline{P}(f_i) = \inf_{P \in \mathscr{M}(\underline{P})} P(f_i)$$

that is if $\underline{P}$ is the lower envelope of $\mathscr{M}$

Thinking in terms of $\mathscr{M}$

If we start by specifying a set $\mathscr{M}$ of probabilities:

- $\underline{P}(f_i)$ equivalent to provide expectation (linear operator) lower bounds
- Set $\mathscr{D}$ of desirable gambles=set of random variables having positive lower expectation, i.e., $\underline{P}(f_i) = 0$

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Probabilities

Probability mass on finite space $\mathscr{X} = \{x_1, \ldots, x_n\}$ equivalent to a n dimensional vector

$$p := (p(x_1), \ldots, p(x_n))$$

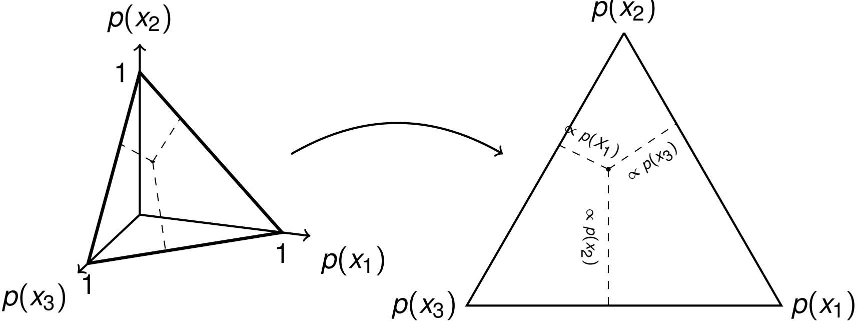
Limited to the set $\mathbb{P}_{\mathscr{X}}$ of all probabilities

$$p(x) > 0, \quad \sum_{x \in \mathscr{X}} p(x) = 1 \quad \text{and}$$

The set $\mathbb{P}_{\mathscr{X}}$ is the $(n-1)$-unit simplex.

Point in unit simplex

$$p(x_1) = 0.2,\ p(x_2) = 0.5,\ p(x_3) = 0.3$$



Imprecise probability

Set $\mathscr{M}$ defined as a set of n constraints

$$\underline{P}(f_i) \leq \sum_{x \in \mathscr{X}} f_i(x)p(x) \leq \overline{P}(f_i)$$

where $f_i :\to \mathbb{R}$ bounded functions

Example

$$p(x_2) - 2p(x_3) \geq 0$$

$$f(x_1) = 0, f(x_2) = 1, f(x_3) = -2, \underline{P}(a) = 0$$

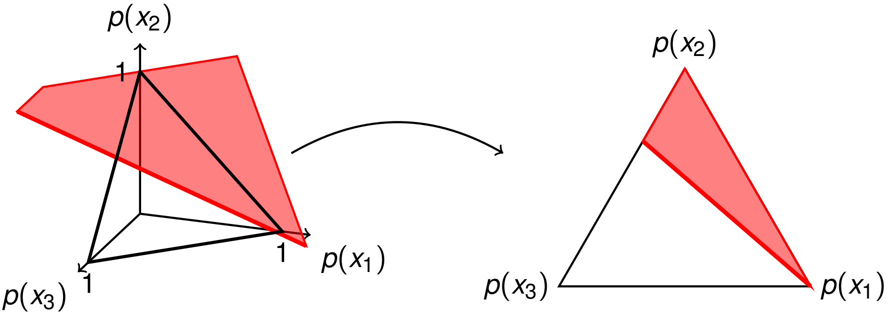
Lower/upper probabilities

Bounds $\underline{P}(A), \overline{P}(A)$ on event A equivalent to

$$\underline{P}(A) \leq \sum_{x \in A} p(x) \leq \overline{P}(A)$$

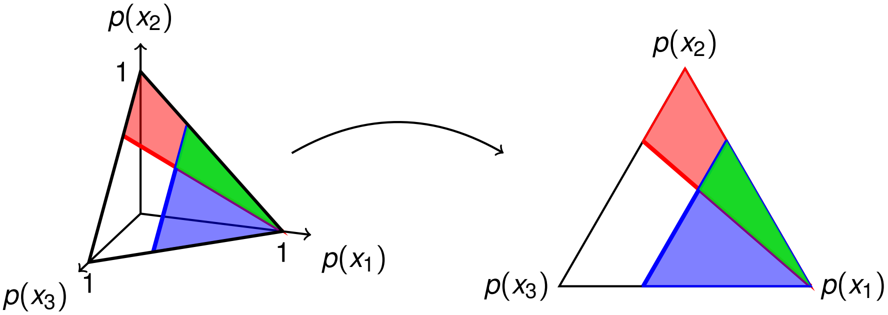
Set $\mathcal{M}$ example

$$p(x_2) \geq 2p(x_3) \Rightarrow p(x_2) - 2p(x_3) \geq 0$$



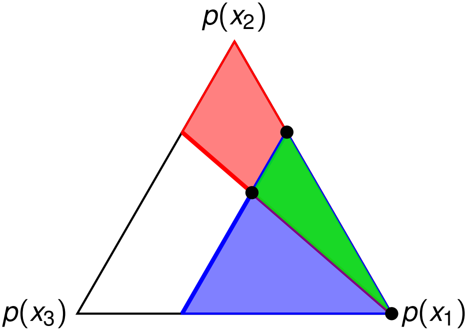
Credal set example

$$p(x_2) - 2p(x_3) \geq 0$$
$$p(x_1) \geq 1/3$$
$$\mathcal{M}$$



Usual alternative presentation: extreme points

- $p(x_1) = 1, p(x_2) = 0, p(x_3) = 0$
- $p(x_1) = 1/3, p(x_2) = 2/3, p(x_3) = 0$
- $p(x_1) = 1/3, p(x_2) = 4/9, p(x_3) = 2/9$



Computing natural extension

- Given $\mathscr{M}$ and a new function g, get

$$\underline{P}(g) = \inf_{P \in \mathscr{M}} P(g) \text{ or } \overline{P}(g) = \sup_{P \in \mathscr{M}} P(g)$$

- First way: linear programming using $\underline{P}(f_i)$

$$\underline{P}(g) = \min_{p(x)} \sum_{x \in \mathscr{X}} p(x)g(x)$$

under

$$\overline{P}(f_i) \geq \sum_{x \in \mathscr{X}} p(x)f_i(x) \geq \underline{P}(f_i)$$

$$\sum_{x \in \mathscr{X}} p(x) = 1, p(x) \geq 0$$

- Second way: compute $\sum_{x \in \mathscr{X}} p(x)g(x)$ for every extreme point, take the minimum

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Why looking at special cases?

- Lower previsions/expectations are quite expressive uncertainty models
- Their general use, especially in large spaces, may require heavy computation (linear optimisation in the best case, often more in complex problems[5])
- Just as Gaussian makes probabilistic computations easier, so does focusing on specific lower previsions

[5] we will see some in the last courses

A first restriction: lower probabilities

- Lower previsions $\underline{P}(f_i)$ are defined for any function $f_i : \mathscr{X} \to \mathbb{R}$.
- Lower probabilities: focusing on events and considering $\underline{P}(A)$, i.e., restrict the space to $2^{\mathscr{X}}$.
- Upper probabilities are dual[6]:

$$\underline{P}(A) = 1 - \overline{P}(A)$$

- Already include a LOT of models used in practice

[6] We can focus on one of the two

A second reduction: 2-monotonicity

A lower probability $\underline{P}()$ is 2-monotone if

$$\underline{P}(A \cup B) + \underline{P}(A \cap B) \geq \underline{P}(A) + \underline{P}(B)$$

- Natural extension/lower expectation of g is given by Choquet integral

$$\underline{P}(g) = \sum_{i=1}^{N} (g(x_{(i)}) - g(x_{(i-1)}))\underline{P}(\{x_{(i)}, \ldots, x_{(N)}\})$$

  with $()$ permutation such that $g(x_{(0)}) = 0, g(x_{(1)}) \leq \ldots \leq g(x_{(N)})$
- Generating extreme points is easy. Take a permutation $()$ of $\{1, \ldots, N\}$ and compute for each i

$$p(x_{(i)}) = \underline{P}(\{x_{(i)}, \ldots, x_{(N)}\}) - \underline{P}(\{x_{(i+1)}, \ldots, x_{(N)}\}),$$

  then p is an extreme point of $\mathscr{M}$

A very practical example: probability intervals

Given lower/upper previsions on the events $\{x\}$,

$$\underline{P}(\{x\}), \overline{P}(\{x\})$$

Easy to check that $\mathscr{M}(\underline{P}) \neq \emptyset$:

$$\sum_x \underline{P}(\{x\}) \leq 1, \sum_x \overline{P}(\{x\}) \geq 1$$

and to check that $\underline{P}$ is coherent:

$$\forall y, \sum_{y \neq x} \underline{P}(\{x\}) + \overline{P}(\{y\}) \leq 1, \sum_{y \neq x} \overline{P}(\{x\}) + \underline{P}(\{y\}) \geq 1$$

A very practical example: probability intervals (cont.)

Natural extension to events very easy:

$$\underline{P}(A) = \max\Big(\sum_{x \in A} \underline{P}(\{x\}), 1 - \sum_{x \notin A} \overline{P}(\{x\})\Big)$$

$$\overline{P}(A) = \min\Big(\sum_{x \in A} \overline{P}(\{x\}), 1 - \sum_{x \notin A} \underline{P}(\{x\})\Big)$$

Interest: $\underline{P}$ can be proved to be 2-monotone

A simple example

Consider the following output of a (credal) classifier:

	x_1	x_2	x_3	x_4
$\overline{P}(\{x_i\})$	0.3	0.4	0.1	0.5
$\underline{P}(\{x_i\})$	0.1	0.1	0	0.2

Does it avoids sure loss? Is it coherent?

What are the lower probabilities of the different events?

Can you compute the lower expectation of
$a(x_1) = 2, a(x_2) = -3, a(x_3) = -1, a(x_4) = 5$?

A third reduction: belief functions

A belief function is a lower probability $\underline{P}$ such that for any collection $\mathscr{A} = \{A_1, \ldots, A_K \subseteq \mathscr{X}\}$ with $K \leq 2^{\mathscr{X}}$, we do have

$$\underline{P}(\cup_{A_i \in \mathscr{A}} A_i) \geq \sum_{\mathscr{B} \subseteq \mathscr{A}} (-1)^{|\mathscr{B}|+1} \underline{P}(\cap_{A_i \in \mathscr{B}} A_i),$$

known as the property of complete (or ∞) monotonicity.

Side exercise: prove that a belief function is also 2-monotone[7]

Side bonus: everything we just said also applies to belief function

[7] In fact, if $\underline{P}$ is k-monotone, it is also (k-1)-monotone.

An interesting tool: Mobius inverse

The Möbius inverse[8] $m : 2^{\mathscr{X}} \to \mathbb{R}$ of a given $\underline{P}$ is

$$m(A) = \sum_{B \subseteq A} (-1)^{|A \setminus B|} \underline{P}(B),$$

and has some interesting properties when applied to belief functions:

- It is bijective with $\underline{P}$ (true for any $\underline{P}$), as for any B

$$\underline{P}(B) = \sum_{A \subseteq B} m(A)$$

- For a new function g, $\underline{P}(g)$ can be computed[9] as

$$\underline{P}(g) = \sum_{A \subseteq \mathscr{X}} m(A) \cdot \inf_{x \in A} g(x)$$

- m is positive (only true for belief functions) → can be seen as a random distribution over subsets → useful tool to simulate $\underline{P}$

[8] Apply in fact to general posets

[9] also applies as long as $\underline{P}$ is 2-monotone

Example 1: frequencies of imprecise observations

Imprecise poll: "Who will win the next Wimbledon tournament?"

∘ N(adal) ∘ F(ederer) ∘ D(jokovic) ∘ M(urray) ∘ O(ther)

60 % replied $\{N, F, D\} \to m(\{N, F, D\}) = 0.6$

15 % replied "I do not know" $\{N, F, D, M, O\} \to m(\mathscr{S}) = 0.15$

10 % replied Murray $\{M\} \to m(\{M\}) = 0.1$

5 % replied others $\{O\} \to m(\{O\}) = 0.05$

...

Another frequentist one

Set of labellers replying between

- ∘ L(ioness) ∘ P(uma) ∘ C(at) ∘ O(celot)

- 25% reply $\{L,P\} \to m(\{L,P\}) = 0.2$
- 10% reply $\{L,P,O\} \to m(\{L,P,O\}) = 0.1$
- 15% reply $\{C,O,P\} \to m(\{C,O,P\}) = 0.15$
- 10% reply $\{L\} \to m(\{L\}) = 0.1$
- 40% reply $\{L,P,C,O\} \to m(\mathscr{S}) = 0.4$

Assess how likely it is to be a lioness, according to opinions

Another frequentist one

Set of labellers replying between

∘ L(ioness) ∘ P(uma) ∘ C(at) ∘ O(celot)

- 25% reply $\{L, P\} \rightarrow m(\{L, P\}) = 0.2$
- 10% reply $\{L, P, O\} \rightarrow m(\{L, P, O\}) = 0.1$
- 15% reply $\{C, O, P\} \rightarrow m(\{C, O, P\}) = 0.15$
- 10% reply $\{L\} \rightarrow m(\{L\}) = 0.1$
- 40% reply $\{L, P, C, O\} \rightarrow m(\mathcal{S}) = 0.4$

Assess how likely it is to be a lioness, according to opinions

$$\underline{P}(\{L\}) = m(\{L\}) = 0.1$$

Another frequentist one

Set of labellers replying between

∘ L(ioness) ∘ P(uma) ∘ C(at) ∘ O(celot)

- 25% reply $\{L,P\} \to m(\{L,P\}) = 0.2$
- 10% reply $\{L,P,O\} \to m(\{L,P,O\}) = 0.1$
- 15% reply $\{C,O,P\} \to m(\{C,O,P\}) = 0.15$
- 10% reply $\{L\} \to m(\{L\}) = 0.1$
- 40% reply $\{L,P,C,O\} \to m(\mathscr{S}) = 0.4$

Assess how likely it is to be a lioness, according to opinions

$$\underline{P}(\{L\}) = m(\{L\}) = 0.1$$

$$\overline{P}(\{L\}) = m(\{L\}) + m(\{L,P,O\}) + m(\{L,P\}) + m(\mathscr{S}) = 0.85$$

Example 2: Imprecise Distributions [4]

A pair $[\underline{F}, \overline{F}]$ of cumulative distributions

Bounds over events $[-\infty, x]$

- Percentiles by experts;
- Kolmogorov-Smirnov bounds;

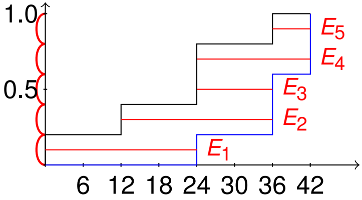
Can be extended to any pre-ordered space [2], [8] $\Rightarrow$ multivariate spaces!

Expert providing percentiles

$$0 \leq P([-\infty, 12]) \leq 0.2$$

$$0.2 \leq P([-\infty, 24]) \leq 0.4$$

$$0.6 \leq P([-\infty, 36]) \leq 0.8$$



A fourth reduction: possibility measure

A possibility measure is a maxitive upper probability $\overline{P}$:

$$\overline{P}(A \cup B) = \max\{\overline{P}(A), \overline{P}(B)\}$$

This has the following consequences:

- All information is encoded in $\overline{P}(\{x\})$, as

$$\overline{P}(A) = \max_{x \in A} \overline{P}(\{x\})$$

- The associated $\underline{P}$ is a belief function
- The sets receiving positive Möbius mass are nested (form a sequence of included sets)

A simple example

A set E of most plausible values

A confidence degree $\alpha = \underline{P}(E)$

Two interesting cases:

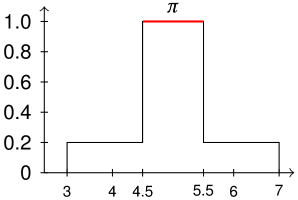
- Expert providing most plausible values E
- E set of models of a formula ϕ

Both cases extend to multiple sets $E_1, \ldots, E_p$:

- confidence degrees over nested sets [6]
- hierarchical knowledge bases [3]

pH value $\in [4.5, 5.5]$ with

$\alpha = 0.8$ ($\sim$ "quite probable")



A simple example

A set E of most plausible values

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Two interesting cases:

- Expert providing most plausible values E
- E set of models of a formula ϕ

Both cases extend to multiple sets $E_1, \ldots, E_p$:

- confidence degrees over nested sets [6]
- hierarchical knowledge bases [3]

variables p, q

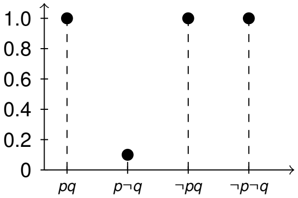
$$\Omega = \{pq, \neg pq, p\neg q, \neg p \neg q\}$$

$$\underline{P}(p \Rightarrow q) = 0.9$$

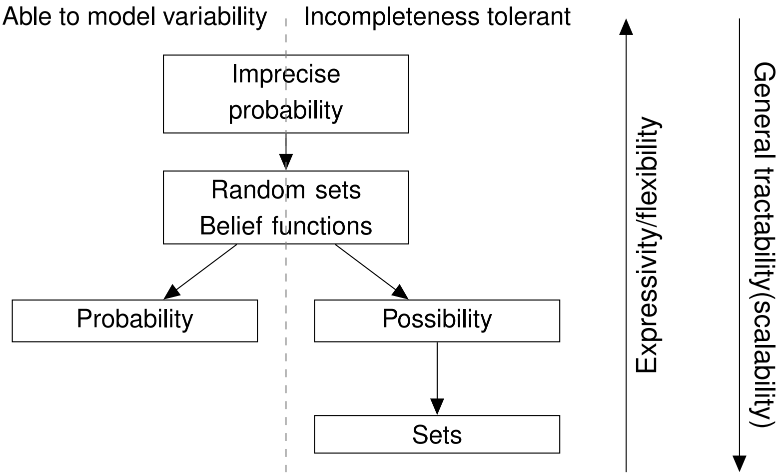
(~ "almost certain")

$$E = \{pq, p\neg q, \neg p \neg q\}$$

- $\pi(pq) = \pi(p\neg q) = \pi(\neg p \neg q) = 1$
- $\pi(\neg pq) = 0.1$



A quick and incomplete summary



Outline

- Basics
- Probabilities as bets
- Going beyond betting probabilities: why and how?
- Probability sets, a.k.a. credal sets
- Practical models and computations
- Decision with probability sets
  - Probabilities
  - Ignorance, complete order
  - Ignorance, partial orders
  - Probability sets with illustration

Decision setting

- Still a set $\mathscr{X}$ of states
- A set $\mathscr{A}$ of actions
- To each action $a : \mathscr{X} \to \mathbb{R}$ corresponds a mapping such that $a(x)$ is the reward/utility of performing a when x is true
- Possibly a set $\mathscr{M}$ modelling our knowledge about X

Decision problem (here): recommend one or multiple actions based on our knowledge about the states in $\mathscr{X}$

An example

What we see when walking at night

- States: the kind of animal
- Actions: what you choose to do

States $\mathscr{X}$

x_1 =(L)ioness x_2 =(P)uma x_3 =(C)at x_4=(O)celot

Actions $\mathscr{A}$

States $\mathscr{X}$

x_1 =(L)ioness x_2 =(P)uma x_3 =(C)at x_4=(O)celot

Actions $\mathscr{A}$

a_1 =(R)un

States $\mathscr{X}$

x_1 =(L)ioness x_2 =(P)uma x_3 =(C)at x_4=(O)celot




Actions $\mathscr{A}$

a_1 =(R)un a_2 =(S)hout


States $\mathscr{X}$

x_1 =(L)ioness x_2 =(P)uma x_3 =(C)at x_4=(O)celot

Actions $\mathscr{A}$

a_1 =(R)un a_2 =(S)hout a_3 =(D)o nothing

The matrix $\mathscr{U}$

	L	P	C	O
R	7	−3	3	5
S	−10	4	4	11
D	−5	−5	5	7

Which action to choose?

Outline

- Basics
- Probabilities as bets
- Going beyond betting probabilities: why and how?
- Probability sets, a.k.a. credal sets
- Practical models and computations
- Decision with probability sets
  - Probabilities
  - Ignorance, complete order
  - Ignorance, partial orders
  - Probability sets with illustration

A quick reminder of expected utility

- Set of states $\mathscr{X}$
- Probability masses $p(x)$ for each state
- Act/decision a maps each state to a utility

$$a : \mathscr{X} \to \mathbb{R}$$

- Expected utility of a

$$P(a) = \sum_x p(x) a(x)$$

An easy decision rule

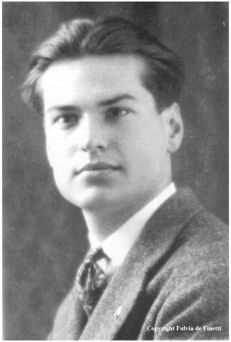
One possible interpretation: $P(a)$ is your price/value[10] of act a, then

$$a \succ b \text{ if and only if } P(a) > P(b)$$

that is, you would "spend" more to buy a than b.

[10] In a linear utility. Quique, que es muy elegante y intelligente, explained it yesterday.

Three important guys



L. Savage [7] J. Von Neumann [9] B. De Finetti [5]

All justify probabilities (and expected utilities) as uncertainty models without frequencies.

An example

This looks like a big animal, so more a puma or lioness than a cat or ocelot ($P(L) = P(P) = 0.3$, $P(C) = P(O) = 0.2$)

	L	P	C	O	$P(a)$
R	7	−3	3	5	2.8
S	−10	4	4	11	
D	−5	−5	5	7	
Max					

$$P(R) = 0.3 \cdot 7 + 0.3 \cdot -3 + 0.2 \cdot 3 + 0.2 \cdot 5 = 2.8$$

An example

This looks like a big animal, so more a puma or lioness than a cat or ocelot ($P(L) = P(P) = 0.3$, $P(C) = P(O) = 0.2$)

	L	P	C	O	$P(a)$
R	7	−3	3	5	2.8
S	−10	4	4	11	1.2
D	−5	−5	5	7	−0.6
Max					2.8

$$R \succ_P S \succ_P D$$

Outline

Maximin: pessimistic behaviour

- For each action a_i, compute $\underline{P}(a_i) = \min_{x_j \in \mathscr{X}} a_i(x_j)$
- Say that $a_k \succ_{Mm} a_\ell$ if $\underline{P}(a_k) > \underline{P}(a_\ell)$

	L	P	C	O	$\underline{P}(a)$
R	7	-3	3	5	-3
S	-10	4	4	11	-10
D	-5	-5	5	7	-5
Max					-3

- We get $R \succ_{Mm} D \succ_{Mm} S$, hence R is recommended
- Pessimistic attitude: best action in the worst case

Why (not) maximin?

Pros:

- Provide strong guarantees on selected option
- Is very-well studied in the literature

Cons:

- Can be very conservative
- Selected option may be suboptimal in all cases

	L	P	C	O	$\underline{P}(a)$
R	7	−3	3	5	−3
S	−10	4	4	11	−10
D	−5	−5	5	7	−5
K	−2	−2	−2	−2	−2
Max					-2

K never the best solution!

Maximax: optimistic behaviour

- For each action a_i, compute $\overline{P}(a_i) = \max_{x_j \in \mathscr{X}} a_i(x_j)$
- Say that $a_k \succ_{MM} a_\ell$ if $\overline{P}(a_k) > \overline{P}(a_\ell)$

	L	P	C	O	$\overline{P}(a)$
R	7	−3	3	5	7
S	−10	4	4	11	11
D	−5	−5	5	7	7
Max					11

- We get $S \succ_{MM} D \approx_{MM} R$, hence S is recommended
- Optimistic attitude: best action in the best case

Why (not) maximax?

Pros:

- Often computationally easier (max/max problem)
- Solution always potentially optimal

Cons:

- May be rather bold (and in our case your last decision)
- Do not provide strong guarantees on reward

In-between: Hurwicz

- Pick a value $\alpha \in [0,1]$, called optimism index
- For a_i, compute

$$u_{H(\alpha)}(a_i) = \alpha \overline{P}(a_i) + (1-\alpha)\underline{P}(a_k)$$

- Say that $a_k \succ_\alpha a_\ell$ if $u_{H(\alpha)}(a_k) > u_{H(\alpha)}(a_\ell)$

	L	P	C	O	$\underline{P}(a_i)$	$\overline{P}(a_i)$	$u_{H(0.5)}(a_i)$
R	7	−3	3	5	−3	7	2
S	−10	4	4	11	−10	11	0.5
D	−5	−5	5	7	−5	7	1
Max							2

- We get $R \succ_{H(0.5)} D \succ_{H(0.5)} S$, hence R is recommended
- Try to balance between optimistic and pessimistic

Why (not) Hurwicz

Pros:

- Try to find a compromise between minimax/maximax
- Well-axiomatised

Cons:

- None of the guarantees of minimax/maximax
- All their defaults, but to a lesser extent
- Operational elicitation of α challenging

Savage Minimax regret

- For action a_i, compute $Re(a_i,x_j) = \max_{a_k \in \mathscr{A}} a_k(x_j) - a_i(x_j)$ the regret of picking a_i in x_j, instead of the best possible action
- For a_i, compute $Re^\star(a_i) = \max_j Re(a_i,x_j)$
- Say that $a_k \succ_{Re} a_\ell$ if $Re^\star(a_\ell) > Re^\star(a_k)$

	L	P	C	O	$Re^\star(a_i)$
R	7	−3	3	5	
$Re(R)$	0				
S	−10	4	4	11	
$Re(S)$					
D	−5	−5	5	7	
$Re(D)$					
Min					

Savage Minimax regret

- For action a_i, compute $Re(a_i, x_j) = \max_{a_k \in \mathscr{A}} a_k(x_j) - a_i(x_j)$ the regret of picking a_i in x_j, instead of the best possible action
- For a_i, compute $Re^{\star}(a_i) = \max_j Re(a_i, x_j)$
- Say that $a_k >_{Re} a_\ell$ if $Re^{\star}(a_\ell) > Re^{\star}(a_k)$

	L	P	C	O	$Re^{\star}(a_i)$
R	7	-3	3	5	
$Re(R)$	0	7			
S	-10	4	4	11	
$Re(S)$					
D	-5	-5	5	7	
$Re(D)$					
Min					

Savage Minimax regret

- For action a_i, compute $Re(a_i, x_j) = \max_{a_k \in \mathscr{A}} a_k(x_j) - a_i(x_j)$ the regret of picking a_i in x_j, instead of the best possible action
- For a_i, compute $Re^\star(a_i) = \max_j Re(a_i, x_j)$
- Say that $a_k >_{Re} a_\ell$ if $Re^\star(a_\ell) > Re^\star(a_k)$

	L	P	C	O	$Re^\star(a_i)$
R	7	−3	3	5	
$Re(R)$	0	7	2	6	7
S	−10	4	4	11	
$Re(S)$					
D	−5	−5	5	7	
$Re(D)$					
Min					

Savage Minimax regret

- For action a_i, compute $Re(a_i,x_j) = \max_{a_k \in \mathscr{A}} a_k(x_j) - a_i(x_j)$ the regret of picking a_i in x_j, instead of the best possible action
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- Say that $a_k >_{Re} a_\ell$ if $Re^\star(a_\ell) > Re^\star(a_k)$

	L	P	C	O	$Re^\star(a_i)$
R	7	−3	3	5	
$Re(R)$	0	7	2	6	7
S	−10	4	4	11	
$Re(S)$	17	0	1	0	17
D	−5	−5	5	7	
$Re(D)$	12	9	0	4	12
Min					

Savage Minimax regret

- For action a_i, compute $Re(a_i, x_j) = \max_{a_k \in \mathscr{A}} a_k(x_j) - a_i(x_j)$ the regret of picking a_i in x_j, instead of the best possible action
- For a_i, compute $Re^\star(a_i) = \max_j Re(a_i, x_j)$
- Say that $a_k \succ_{Re} a_\ell$ if $Re^\star(a_\ell) > Re^\star(a_k)$

	L	P	C	O	$Re^\star(a_i)$
R	7	−3	3	5	
$Re(R)$	0	7	2	6	7
S	−10	4	4	11	
$Re(S)$	17	0	1	0	17
D	−5	−5	5	7	
$Re(D)$	12	9	0	4	12
Min					7

- We get $R \succ_{Re} D \succ_{Re} S$, hence R is recommended
- Minimize regret, but sensitive to addition of non-optimal alternatives

Minimax regret vs maximin

Consider the following case:

	x_1	$\cdots$	x_{99}	x_{100}	$R^\star(a_i)$	$\underline{P}(a_i)$
a_1	10	$\cdots$	10	1		
$R(a_1)$						
a_2	2	$\cdots$	2	2		
$R(a_2)$						
Min						

Minimax regret vs maximin

Consider the following case:

	x_1	$\cdots$	x_{99}	x_{100}	$R^\star(a_i)$	$\underline{P}(a_i)$
a_1	10	$\cdots$	10	1		1
$R(a_1)$	0	$\cdots$	0	1	1	
a_2	2	$\cdots$	2	2		2
$R(a_2)$	8	$\cdots$	8	0	8	
Min					1	2

- Maximin: a_2
- Minimax regret: a_1

Minimax regret and irrelevant alternatives

Before: $R \succ_{Re} D \succ_{Re} S$

Now I get (A)nti-puma!

	L	P	C	O	$Re^{\star}(a_i)$
R	7	-3	3	5	
$Re(R)$					
S	-10	4	4	11	
$Re(S)$					
D	-5	-5	5	7	
$Re(D)$					
A	-15	15	-2	0	
$Re(A)$					
Min					

After A is possible:

Minimax regret and irrelevant alternatives

Before: $R \succ_{Re} D \succ_{Re} S$

Now I get (A)nti-puma!

	L	P	C	O	$Re^{\star}(a_i)$
R	7	−3	3	5	
$Re(R)$	0	18	2	6	18
S	−10	4	4	11	
$Re(S)$	17	11	1	0	17
D	−5	−5	5	7	
$Re(D)$	12	10	0	4	12
A	−15	15	−2	0	
$Re(A)$	22	0	5	11	22
Min					12

After A is possible: $D \succ_{Re} S \succ_{Re} R \succ_{Re} A$ (change on preferences not involving A)

Complete ordering: summary

- Minimax=pessimistic [10]
- Maximax=optimistic
- Hurwicz=in-between [1]
- Savage=Minimizing felt regret [7]

Whatever the chosen rule, we always get one optimal action. But we need to commit to a peculiar behaviour.

What if DM does not want to commit to peculiar behaviour?

What if DM wants to only know the actions that are potentially optimal, given our uncertainty?

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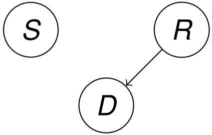
Lattice ordering

- Say that $a_k \geq_L a_\ell$ if $\overline{P}(a_k) \geq \overline{P}(a_\ell)$ and $\underline{P}(a_k) \geq \underline{P}(a_\ell)$

	L	P	C	O	$\underline{P}(a_i)$	$\overline{P}(a_i)$
R	7	−3	3	5	−3	7
S	−10	4	4	11	−10	11
D	−5	−5	5	7	−5	7



- Only existing dominance is D by R, hence only D is considered non-optimal
- Can be seen as a robust Hurwicz (considering all α as possibilities)
- Note that with this criterion, we eliminate the best action in state C
- This rule looks good, why should I not use it?

Information-monotonic preferences

Principle

A (partial) decision rule is information monotonic if gaining more information can only refine our current preferences

Definition for imprecise information

A decision rule $\geq$ is information monotonic if for any pair of actions a, b and for $E' \subseteq E$, we have

$$(E \implies a \geq b) \implies (E' \implies a \geq b),$$

meaning that the preference relation can only be refined by getting more precise

Lattice ordering and information monotonicity

	x_1	x_2	x_3	x_4	$\underline{P}(a_i)$	$\overline{P}(a_i)$
a	10	12	14	15	10	15
b	13	11	16	14	11	16

$$b \succ a$$

All states possible

Lattice ordering and information monotonicity

	$\cancel{x_1}$	x_2	x_3	x_4	$\underline{P}(a_i)$	$\overline{P}(a_i)$
a	$\cancel{10}$	12	14	15	12	15
b	$\cancel{13}$	11	16	14	11	16

$$b >< a$$

We learn (gain info) x_1 impossible

a and *b* becomes incomparable.

Lattice ordering and information monotonicity

	~~x_1~~	x_2	~~x_3~~	x_4	$\underline{P}(a_i)$	$\overline{P}(a_i)$
a	~~10~~	12	~~14~~	15	12	15
b	~~13~~	11	~~16~~	14	11	14

$$b \prec a$$

We learn (gain info) x_3 impossible

a is now preferred to b.

Refining Pareto

Principle

A (partial) decision rule refines Pareto if it ensures that its preference order refines Pareto dominance

Definition for imprecise information

A decision rule $\succeq$ refines Pareto if for any pair of actions a, b

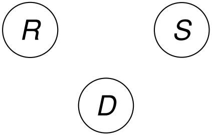
$$a \succeq_P b \implies a \succeq b,$$

where $\succeq_P$ is Pareto dominance

Interval dominance

- Say that $a_k \succ_{ID} a_\ell$ if $\underline{P}(a_k) > \overline{P}(a_\ell)$

	L	P	C	O	$\underline{P}(a_i)$	$\overline{P}(a_i)$
R	7	−3	3	5	−3	7
S	−10	4	4	11	−10	11
D	−5	−5	5	7	−5	7

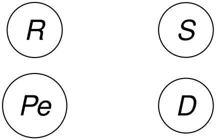


- no dominance at all
- overcautious criterion → may retain Pareto-dominated solutions

Interval dominance: drawback example

- We add a fourth possible action *Pe*=Pet the animal

	L	P	C	O	$\underline{P}(a_i)$	$\overline{P}(a_i)$
R	7	−3	3	5	−3	7
S	−10	4	4	11	−10	11
D	−5	−5	5	7	−5	7
Pe	−5	−5	2	−5	−5	2

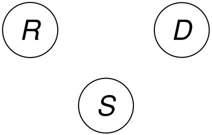


- no dominance, all intervals intersect
- even if *D* better (sometimes strictly) than *Pe* in **every** situation!

Difference dominance

- Say that $a_k \succeq_D a_\ell$ if $a_k(x_j) - a_\ell(x_j) \geq 0$ for all x_j ($\succ$ if > 0 for at least one x_j)

	L	P	C	O
R	7	−3	3	5
S	−10	4	4	11
D	−5	−5	5	7
$R - S$	17	−7	−1	−6



- no dominance at all, again
- do we have the same problem as with interval dominance?

Difference comparison

- We add a fourth possible action *Pe*=Pet the animal

	L	P	C	O
R	7	−3	3	5
S	−10	4	4	11
D	−5	−5	5	7
Pe	−5	−5	2	−5
$D - Pe$	0	0	3	12

$$
\begin{tikzcd}
R \arrow[rr] & & Pe \\
D \arrow[urr] & & S \arrow[u]
\end{tikzcd}
$$

- In the ignorance case, exactly Pareto ordering!

So far. . .

Options when true state of the world completely unknown:

- Complete ordering/one top recommendation
  - Maximin: pessimistic DM
  - Maximax: optimistic DM
  - Hurwicz: attempt to in-between
  - Regret minimax: pessimistic DM w.r.t. regret
- Partial ordering/multiple recommendations reflecitng lack of knowledge
  - Lattice ordering: robust hurwicz, may miss potentially optimal actions
  - Difference dominance: will keep every non-Pareto dominated solution
  - Interval dominance: very conservative, may keep Pareto dominated options

A summary of the different rules

Property	$\succ_{Mm}$	$\succ_{MM}$	$\succ_{R}$	$\succ_{H(\alpha)}$	$\succ_{L}$	$\succ_{D}$	$\succ_{ID}$
Complete	✓	✓	✓	✓	x	x	x
Reco possibly optimal	x^*	✓	x^*	x^*	✓	✓	✓
Guaranteed value	✓	x	✓	x	$N.A.$	$N.A.$	$N.A.$
$a \succ b$ depends only on a, b	✓	✓	x	✓	✓	✓	✓
Refines Pareto	✓	✓	✓	✓	✓	✓	x
Information monotonic	x	x	x	x	x	✓	✓

We also have $\succ_L \subseteq \succ_D \subseteq \succ_{ID}$, going from the most precise to the least

$*$ Not guaranteed to be.

Outline

Previous decision rules adaptation

In general, replace u^* by upper expectation $\overline{P}$, u_* by lower expectation $\underline{P}$

Total order

- Maximax: $a \succeq_{MM} b$ if $\overline{P}(a) \geq \overline{P}(b)$
- Maximin: $a \succeq_{Mm} b$ if $\underline{P}(a) \geq \underline{P}(b)$
- Hurwicz: $a \succeq_{\alpha} b$ if $\alpha\overline{P}(a) + (1-\alpha)\underline{P}(a) \geq \alpha\overline{P}(b) + (1-\alpha)\underline{P}(b)$

Partial order

- Interval dominance: $a \succ_{ID} b$ if $\overline{P}(b) \leq \underline{P}(a)$
- Lattice: $a \succ_{L} b$ if $\overline{P}(b) \leq \overline{P}(a) \wedge \underline{P}(b) \leq \underline{P}(a)$
- Difference: $a \succ_{D} b$ if $\underline{P}(a-b) \geq 0$

Difference dominance

Under knowledge $\mathscr{P}$, action a_k is better than a_ℓ if

$$\underline{P}(a_k - a_\ell) = \inf_{p \in \mathscr{P}} P(a_k - a_\ell),$$

that is if in average, we gain something when exchanging a_ℓ for a_k

Special cases

- probabilities $\equiv$ expected utility
- set $\equiv$ difference dominance (filter out Pareto-dominated solutions)

E-admissibility

- Previous rules use orderings between alternatives
- Another way: pick potentially optimal answers
- For a given set $\mathscr{A}$ of actions and a probability p, let

$$Opt(P, \mathscr{A}) = \arg\max_{a \in \mathbb{A}} P(a)$$

- The E-admissible rule returns the set

$$Opt_E(\mathscr{M}, \mathscr{A}) = \cup_{P \in \mathscr{M}} Opt(P, \mathscr{A})$$

Links between rules

Given $\succ_i$, we denote $Opt_{\succ_i}(\mathscr{M},\mathscr{A}) := \{a \in \mathbb{A} : \nexists a' \text{ s.t. } a' \succ_i a\}$ its set of maximal elements.

We have the following relations:

- $a \succeq_{ID} b \implies a \succeq_D b \implies a \succeq_L b \implies a \succeq_\alpha b \quad \forall \alpha$
- $Opt_E(\mathscr{M},\mathscr{A}) \subseteq Opt_{\succ_D}(\mathscr{M},\mathscr{A}) \subseteq Opt_{\succ_{ID}}(\mathscr{M},\mathscr{A})$
- $Opt_{\succ_\alpha}(\mathscr{M},\mathscr{A}) \subseteq Opt_{\succ_L}(\mathscr{M},\mathscr{A}) \subseteq Opt_{\succ_D}(\mathscr{M},\mathscr{A})$

As an exercice, prove the implications of the first line, and the first inclusion of the second (other inclusions immediately follow from implications).

Back to Ellsberg

9 balls, 3 are reds, 6 remaining are either yellow or black

A

R(ed)	B(lack)	Y(ellow)
100 $	0 $	0$

B

R(ed)	B(lack)	Y(ellow)
0 $	100 $	0$

C

R(ed)	B(lack)	Y(ellow)
100 $	0 $	100$

D

R(ed)	B(lack)	Y(ellow)
0 $	100 $	100$

- What are the possible probability values? In terms of bounds over each colour?
- Compute the lower/upper expectations for each act
- What kind of comparison explain the most frequent behaviour $A \geq B$ but $D \geq C$?

A more elaborate example

Set of labellers replying between

∘ L(ioness) ∘ P(uma) ∘ C(at) ∘ O(celot)

- 20% reply $\{L, P\} \rightarrow m(\{L, P\}) = 0.2$
- 10% reply $\{L, P, O\} \rightarrow m(\{L, P, O\}) = 0.1$
- 15% reply $\{C, O, P\} \rightarrow m(\{C, O, P\}) = 0.15$
- 10% reply $\{L\} \rightarrow m(\{L\}) = 0.1$
- 40% reply $\{L, P, C, O\} \rightarrow m(\mathscr{S}) = 0.4$

Back to our issue: example of some rules (not all)

Is R better than S, or the other way around?

	L	P	C	O
Run	7	−3	3	5
Shout	−10	4	4	11
Do nothing	−5	−5	5	7

- $m(\{L,P\}) = 0.2$
- $m(\{L,P,O\}) = 0.1$
- $m(\{C,O,P\}) = 0.15$
- $m(\{L\}) = 0.1$
- $m(\mathscr{S}) = 0.4$

Evaluation: averaging utility + attitude (pessimist/optimist/robust)

Back to our issue: example of some rules (not all)

Is R better than S, or the other way around?

	L	P	C	O
Run	7	−3	3	5
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- $m(\{L,P\}) = 0.2$
- $m(\{L,P,O\}) = 0.1$
- $m(\{C,O,P\}) = 0.15$
- $m(\{L\}) = 0.1$
- $m(\mathscr{S}) = 0.4$

Evaluation: averaging utility + attitude (pessimist/optimist/robust)

$$\underline{P}(Run) = 0.2 \times -3 + 0.1 \times -3 + 0.15 \times -3 + 0.1 \times 7 + 0.4 \times -3 = -2$$
$$\underline{P}(Shout) = 0.2 \times -10 + 0.1 \times -10 + 0.15 \times 4 + 0.1 \times -10 + 0.4 \times -10 = -7.9$$

Seems better to Run than Shout

Back to our issue: example of some rules (not all)

Is R better than S, or the other way around?

	L	P	C	O
Run	7	−3	3	5
Shout	−10	4	4	11
Do nothing	−5	−5	5	7

- $m(\{L,P\}) = 0.2$
- $m(\{L,P,O\}) = 0.1$
- $m(\{C,O,P\}) = 0.15$
- $m(\{L\}) = 0.1$
- $m(\mathcal{S}) = 0.4$

Evaluation: averaging utility + attitude (pessimist/optimist/robust)

$$\overline{P}(Run) = 0.2 \times 7 + 0.1 \times 7 + 0.15 \times 5 + 0.1 \times 7 + 0.4 \times 7 = 6.7$$
$$\overline{P}(Shout) = 0.2 \times 4 + 0.1 \times 11 + 0.15 \times 11 + 0.1 \times -10 + 0.4 \times 11 = 6.95$$

Seems better to Shout than Run

Back to our issue: example of some rules (not all)

Is R better than S, or the other way around?

	L	P	C	O
Run	7	−3	3	5
Shout	−10	4	4	11
Do nothing	−5	−5	5	7

- $m(\{L,P\}) = 0.2$
- $m(\{L,P,O\}) = 0.1$
- $m(\{C,O,P\}) = 0.15$
- $m(\{L\}) = 0.1$
- $m(\mathscr{S}) = 0.4$

Evaluation: averaging utility + attitude (pessimist/optimist/robust)

$$[\underline{P}(Run), \overline{P}(Run)] = [-2, 6.7]$$
$$[\underline{P}(Shout), \overline{P}(Shout)] = [-7.9, 6.95]$$

Not entirely clear what is the best (as Puma and Lion are both likely)

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